Resilience Modeling and Management of Wind Turbine Parks

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ABSTRACT

Over the recent decade increased research efforts have been directed on the modelling of resilience of industrial and/or technical systems in their context, i.e. socio-technical systems. The present paper presents a generic resilience model framework for the support of design and integrity management of such systems. The modelling framework is formulated, presented and illustrated with specific consideration of wind turbine parks which encompass many of the characteristics of large-scale complex industrial and infrastructure systems. The basis is a system of systems model which in the present application is comprised of wind turbine parks, each including a finite number of wind turbines which in turn all are systems of different types of subsystems, such as mechanical subsystems, electrical subsystems and structural subsystems. Two levels of dependencies are included in the system resilience modelling, namely between turbines and between turbine subsystems. Furthermore, the evolution of the performance, together with the expected value of benefits and losses, as well as the capacity of wind turbine parks over time is described. On this basis the resilience modeling is formulated considering the performances of and the interactions between wind turbine parks, the organization responsible for integrity management and regulations. Finally an example is presented considering the modeling and analysis of the resilience of one wind turbine park for the purpose of optimizing resilience management. Parameter studies are presented illustrating the how the resilience performance may be optimized by means of adjusting the reliability of subsystems as well as through allocation of income for coverage of costs of future inspections, maintenance and renewal works.

1 INTRODUCTION

Resilience of systems has attained significant interest over the last 2-3 decades across the natural, social, human and engineering sciences, see e.g. Derissen et al. (2011), Linkov et al. (2014), Qin et al. (2017) and Faber et al. (2018). Whereas, within the different sciences, the systems of interest are of rather diverse characteristics, there is general agreement with respect to the concept. Resilience is commonly understood as an aggregate characterization of systems encompassing their ability to maintain their main modes and levels of services, to develop and mobilize resources to adapt to and sustain disturbances over time.

Research on resilience within the engineering sciences has been focusing on the modeling of how engineered systems are able to sustain one given disturbance scenario, how, to which extent and by when the organizations managing them are able to reestablish their functionalities and not least the losses associated with disruptions and rehabilitations. Knowledge in this respect greatly facilitates the understanding of how engineered systems in their organizational context may be designed and managed optimally for given individual events of disturbances, such as historical earthquake, flood and storm events. With this basis, moreover, the statistical characteristics of the mentioned system performances with respect to all relevant, and in principle unknown individual disturbance events, may be assessed by probabilistic modeling and analysis.

In Faber et al. (2017), system resilience is addressed from a more holistic perspective, addressing not only one (probably random) event of a given disturbance scenario but rather all possible time histories of disturbance events over the lifetime of the systems, and thereby facilitates the modeling of the generation of time-variant net benefit provided by systems. This formulation in turn makes it possible to model the capacity of the systems over time and thus opens up to represent and assess resilience failure events from a probabilistic perspective. System resilience failure events are thus defined as the events where the available accumulated capacities of the system are exhausted by the demands associated with the disturbance events - where capacities and demands may relate to economy, human resources and environmental resources.

In the present paper we build on the formulation of system resilience model from Faber et al. (2017) and adapt this to address wind turbine parks. In section 2, closely following JCSS (2008), the system representation of wind turbine parks will be introduced briefly, which is formulated as a two level hierarchy of systems. At the low level there are the mechanical, electrical and structural subsystems comprising the individual wind turbines and at the high level there is the wind turbine park comprised by the individual wind turbines. Correspondingly, two levels of dependency within the wind turbine park performance are accounted for in the system representation. Section 3 outlines an analytical framework for the probabilistic modeling and analysis of resilience of wind turbine parks. It is assumed that the considered hierarchical system is managed by an owner/operator organization and the resilience performance of the system is modelled and assessed with respect to different decision alternatives with respect to target reliability of design, budgeting of renewals and maintenance, stock keeping of essential spare parts and availability of human resources for rehabilitation and maintenance activities. In Section 4, an example is provided to illustrate the resilience analysis of a wind turbine park composed by 10 wind turbines and the influence by preparedness level, target design reliability and the accumulated capacity.

2 SYSTEM REPRESENTATION OF WIND TURBINE PARKS

The basis of the resilience modeling of wind turbine parks is the system representation, which in turn depends on the system representations of the individual wind turbines as well as the dependency between individual wind turbines and between the subsystems constituting these. As shown in Figure 1, wind turbines are complex systems themselves, typically composed by many subsystems or components such as blades, brakes, gearbox, generator and tower. Those components can generally be categorized into several different type of subsystems, i.e. the mechanical, electrical and structural subsystems. The performance of individual wind turbines critically depends on the joint performance of all of such subsystems. That is, the system of wind turbines generally may be considered a system of systems. For what concerns the electrical subsystems and mechanical subsystems, system models are traditionally established using e.g. Failure Mode and Effect Analysis (FEMA) or Failure Tree Analysis (FTA), see e.g. Tavner et al. (2007) and Sørensen & Toft (2010). For the structural subsystem of each individual wind turbine, there are different types of members such as tower, main frame, blades and foundation. A number of different failure modes of the structural subsystem must be considered, such as foundation failure, fatigue crack growth, tower bending failure, tower buckling failure, blade fatigue failure, blade delamination, etc. The relevant failure modes and the event of subsystem failure may be represented in a probabilistic analysis through union and intersections of individual failure modes represented by limit state equations.

In principle, the system representations and the probabilistic models for the different failure modes of individual wind turbines are identical in their general structure, and only the probabilistic representations of the variables entering into the limit state functions may be different. Concerning the performance of wind turbine parks, the dependencies from wind turbine to wind turbine must be accounted for. These dependencies may be addressed at two levels, i.e. turbine level dependency (the dependency between the performances of individual wind turbines) and subsystem level dependency (the dependency between the performances of subsystems). Wind turbines located in the same wind turbine park, are generally subject to similar environmental loads and natural hazard events, e.g. similar intensities of wind, waves and wind waves for offshore wind turbines, earthquakes why also operational demands on e.g. generators and gearboxes are dependent. Moreover, wind turbines within one wind turbine park are subject to the same general strategies with respect to monitoring, control, maintenance and renewals. At subsystem level, subsystems of one wind turbine work together and the change of the condition state of one or more subsystems may cause that of the other subsystems in a cascading manner. The scheme for the representation of systems of wind turbine parks considering two levels of dependency is shown briefly in Figure 2.

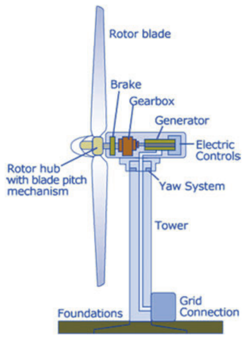

Figure 1: *Illustration of a typical wind turbine (www.connectorsupplier.com)*

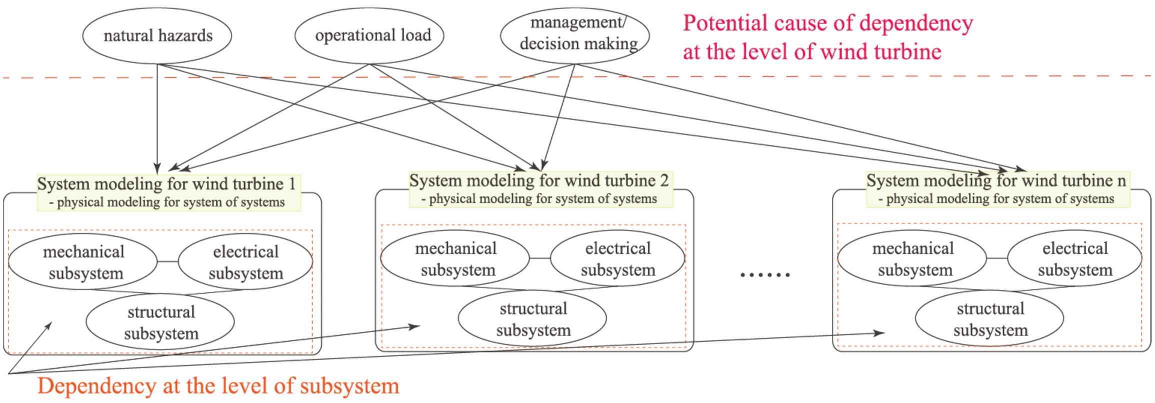

Figure 2: *System representation of wind turbine parks considering two levels of dependency*

Two directions for the probabilistic assessment of the performances of wind turbines are available from the literature, namely i) the top down collection and statistical analysis of the performance data, see e.g. Tavner et al. (2007), and ii) the phenomenological probabilistic modeling and evaluation, see e.g. Arwade et al. (2011), Leite et al. (2006) and Sørensen & Toft (2010). Within the German "250 MW Wind" test program a database of observed turbine reliabilities is made publicly available on the website: www.windmonitor.de. Analysis based on this database may be found in, for example, Tavner et al. (2006), Tavner et al. (2007) and Echavarria et al. (2008). Typically, failure events for wind turbines are interpreted using the power law process (PLP) or homogeneous Poisson process (HPP), see e.g. Tavner et al. (2007) for details. Especially for structural subsystems, the probabilistic analysis in the context of reliability assessment and design are presented in Sørensen & Toft (2010).

3 RESILIENCE ANALYSIS FRAMEWORK

For important infrastructure systems such as wind turbine parks, whose performance is of increasing importance for the reliable fulfillment of the electricity demand of society, the reliability of their service provision over time should be a main concern, rather than the traditional focus on the reliability of individual wind turbines or subsystems hereof. Faber et al. (2017) considers the resilience of engineered systems from a service life perspective and models the evolution of service provision and associated benefit generation together with the capacities of the system (organizational, economic and/or ecological) over time. Resilience failure is defined as the event that one or more of the capacities are exceeded by demands and/or the consequences of disturbances.

Figure 3 illustrates the resilience model proposed in Faber et al. (2017), in which for illustrative purposes the economic capacity of a system is assumed generated by accumulating a fixed percentage $\chi\%$ of the economic output (benefit) provided by the service provision of the system. It is assumed that a startup capacity is available at time $t = 0$. This is taken as $\chi\%$ of the expected value of the annually generated benefit considering all relevant disturbance events over the service life of the system. Disturbance events may cause damage to the system and correspondingly the benefit generation will be reduced for a period of time. The first immediate drop in the benefit rate after a disturbance event, see Figure 3, may be noticed to relate directly to system reliability and robustness. The accumulated reserves will decrease to support the recovery activities. The time history with a green line corresponds to an event of resilience failure, i.e. the disturbance event exhausts the accumulated reserves.

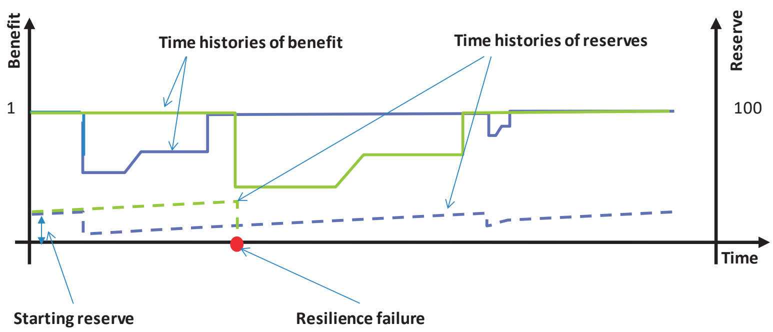

Figure 3: *Illustration of resilience model in terms of evolution of benefit and corresponding evolution of accumulated reserves with time (Faber et al. (2017))*

Following Faber et al. (2017), the limit state function of the event of resilience failure at time t could be expressed as:

$$g_{\mathrm{RF}}(t) = r_r\left(\mathbf{X}(t),\mathbf{a}\right) - s_r\left(\mathbf{X}(t),\mathbf{a}\right) \tag{1}$$

where r_r and s_r are functions representing the capacity and the demand of the system at time t, respectively. The demand is in principle any event with the potential to reduce the capacity of the system, typically referred to as disturbances. It should however, be noted that not only sudden and large consequence events are of relevance, but also effects of e.g. slowly evolving degradation and lack of efficiency in integrity management may be critically important. $\mathbf{X}(t)$ is a vector of random variables which in general depend on time and $\mathbf{a}$ is a vector containing all decision alternatives which may affect the resilience performance of the system. The probability that this function g_{RF}, for the first time during a considered reference period (service life), attains a negative value represents the probability of resilience failure of the system. Generally, it is rather non-trivial to assess this first excursion probability explicitly, however, Monte Carlo simulations may be adequately applied.

The resilience modeling introduced here is formulated for general socio-technical systems and may be adapted to address the resilience analysis of wind turbine parks. The evolution of benefit and reserve with time represented here may be applied for the modelling of wind turbine parks directly. However, the definition of the shape of the benefit generation losses caused by disturbance events, e.g. the total loss and also the time spent on the recovery, depend on the characteristics of the damage, i.e. the type of subsystems damaged, the response of the organizational system and the regulatory system, as illustrated in the example presented in the following section. Based on the evolution of benefit and reserve with time of all the wind turbines belonging to the same wind turbine park, the evolution of benefit and reserve with time for the entire wind turbine park may be obtained. The two levels of dependencies introduced in the foregoing section must be taken into account, which will also be explained in the subsequent investigations.

4 EXAMPLE

In this section, the resilience assessment of one offshore wind turbine park with 10 identical wind turbines is considered. The service life for the individual wind turbines is set to be 30 years. For illustrational purpose, each wind turbine in the considered wind turbine park is composed by three different subsystems, namely the electrical subsystem (such as generator and electrical control), the mechanical subsystem (such as mechanical brake and gearbox) and the structural subsystem (such as main shaft and rotor blade). The structural subsystems are assumed to be exposed to environmental load disturbances such as wind and waves; while the electrical subsystems and mechanical subsystems have their respective capacities to withstand the operational demands. It is assumed here that the failure rate with respect to the operational load of the subsystems of all the wind turbines of this park, defined as the reciprocal of the mean time between failure (MTBF), lies on the constant part of a bathtub curve and remains constant over time. Furthermore the performance of each subsystem is described by a homogeneous Poisson process (HPP) model, see e.g. Tavner et al. (2007) and Sørensen & Toft (2010) for reference. That is, the long-term effect of the subsystem capacity such as fatigue is not considered here in this investigation. It is assumed that all the wind turbines in the wind turbine park are designed and built simultaneously. They are subject to the same demands and disturbances and managed by the same operator and in accordance with the same management strategy. It is further assumed that the failure of the electrical subsystem or the mechanical subsystem of one wind turbine may produce extra loads on its structural subsystem and make it fail also. The conditional failure probability of the structural subsystem of one wind turbine given that its electrical subsystem or mechanical subsystem fails is shown in Table 3, which is dependent on the target level of design.

The structural subsystems are assumed to be exposed to environmental load disturbances L_H. The capacity of a structural subsystem, in this regard, r_H, is modelled by a log-normal distribution random variable. The expected value and the coefficient of variation of r_H are 1 and 0.3 respectively. The limit state function representing the failure event of the individual structural subsystems with respect to the environmental load disturbances is:

$$g_H = z_1 r_H - L_H \tag{2}$$

where z_1 is design parameter calibrated to comply with the requirements to the target reliabilities of wind turbines.

The occurrences of the environmental disturbance events are assumed to follow a Poisson process with annual rate $\lambda_H = 3$. The intensities of disturbance events acting on each wind turbine within the wind turbine park is modelled by a random vector $\mathbf{I}_H$ with constituents assumed to be Gumbel distributed. The intensities of the disturbance $\mathbf{I}_H$ acting on different wind turbines in this park at a given time are correlated with correlation coefficient ρ_{I_H}. The expected values and the coefficients of variation of the intensity I_H, i.e. $E\left[I_H\right]$ and $COV\left[I_H\right]$, are equal to 1 and 0.4, respectively; the correlation coefficient ρ_{I_H} is 0.8.

Given a disturbance event, each subsystem has two condition states, i.e. 'survival' and 'failure'. Failure of any subsystem of one wind turbine implies total loss of service from that turbine. The performance of one wind turbine may thus be modelled through a series system as illustrated in Figure 4 where also the demands and disturbances acting on the subsystems are indicated. If one wind turbine performs well (no subsystem fails), it provides its anticipated service, i.e. it generates electricity in accordance with design specifications. The benefit per unit time (year) provided by one wind turbine is assumed to be equal to one if it performs well. It is assumed that the subsystems are replaced upon their failure and the replacement costs of different types of subsystems are given in Table 1.

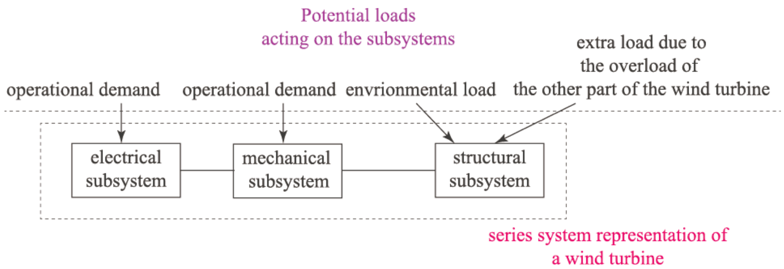

Figure 4: *Illustration of the series system representation of a wind turbine*

Table 1: Replacement cost for different type of subsystems

Type of subsystems	Replacement cost
Electrical subsystem	0.6
Mechanical subsystem	0.4
Structural subsystem	2

The evolution of the functionality provided by one wind turbine for a particular realization of a disturbance event is illustrated in Figure 5 (adapted from Faber et al. (2017)). The functionality is reduced by ΔB_1 at the time of the disturbance. ΔT_1 represents the period from the realization of the disturbance till the functionality of the wind turbine has been re-established. The evolution of the functionality of the whole wind turbine park is simply the sum of that of individual wind turbines.

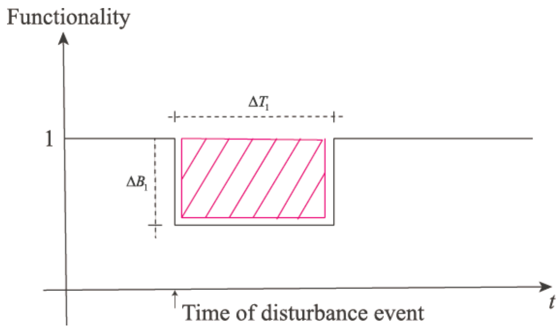

Figure 5: *Illustration of the reorganization and recovery of the functionality of a wind turbine for a particular realization of a disturbance event*

The loss of functionality of wind turbines ΔB_1 for a particular disturbance is considered to be the ratio of the loss of benefit to the total benefit of the original wind turbine. Note that ΔB_1 will be equal to 1 here if one or more of those three types of subsystems fails based on the assumption that the wind turbine will then stop to work. The period ΔT_1 describing the principal service loss and recovery curve is modelled by a log-normal distributed random variable. Two levels of preparedness of the operator organisation to deal with the damage caused by the disturbance event are considered, i.e. low and high, which affect the rapidity of the recovery. The expected value $E[\cdot]$ and the coefficient of variation $COV[\cdot]$ for the period ΔT_1 vary with the preparedness levels and the cause of the failure of the wind turbine, i.e. the failure of the subsystems leading to the loss of service of the wind turbine. A high preparedness level implies relatively small expected value of the recovery period and also low coefficient of variation; while a low preparedness level has the opposite effect. Replacement activities for the structural subsystems are generally rather involving and take a long time compared with other subsystems. Simultaneous failure of more than one subsystem may take place in which case it is assumed that the recovery time for the wind turbine is equal to the recovery period of the subsystem with the longest recovery time. The probabilistic model for the recovery period is provided in Table 2.

Table 2: Definition of the probabilistic model of the recovery period ΔT_1 with respect to the type of subsystems that stops the turbine to work as well as preparedness level

Variable	Distribution	Low preparedness				High preparedness			
		Expected value			COV	Expected value			COV
		Structural subsystem	Electrical subsystem	Mechanical Subsystem		Structural subsystem	Electrical subsystem	Mechanical subsystem	
ΔT_1	log-normal	ΔB_1	$\Delta B_1 / 3$	$\Delta B_1 / 3$	0.2	$\Delta B_1 / 2$	$\Delta B_1 / 6$	$\Delta B_1 / 6$	0.1

As earlier outlined it is assumed that the economic capacity is accumulated over the service life of the wind turbine park to support the replacement of the wind turbines and subsystems which may fail due to the operational loads or the environmental load disturbances. The economic capacity at the beginning of the service life is assumed equal to a percentage $\chi\%$ of the expected value of the accumulated benefits over the service life of the park.

In the following, the resilience of the wind turbine park is analyzed to investigate the influence of the target level of the design reliability for environmental load disturbances and the operational load, which are calibrated by the values of z_1 and MTBF respectively, preparedness level and the percentage $\chi\%$. The resilience is quantified by the probability of resilience failure (the exhaustion of the economic capacity accumulated by the system of time) within the 30-year service life in dependency of the percentage χ %. Wind turbines with two different levels of target reliability are considered in the investigation and the corresponding values of the relevant parameters relevant to the reliability of structural subsystems and the reliability of the other two types of subsystems are provided in Table 3 and Table 4 respectively. The two groups of values of MTBF defined in Table 4 are taken from Tavner et al. (2007) corresponding to the statistical analysis of the 10-year data of the reliability of wind turbines in Denmark and Germany respectively.

Table 3: Parameters relevant to the design reliability of structural subsystems with different target levels

Target level of design	Reliability calibration to environmental load		Conditional failure probability of the structural subsystem given the failure of the electrical subsystem or the mechanical subsystem of the same wind turbine
	Probability of failure due to environmental load $\Pr(g_H < 0)$	z_1	
High target level	1.1×10^{-3}	3.5	0.1
Low target level	1.2×10^{-2}	2.5	0.3

Table 4: Values of MTBF of electrical subsystems and mechanical subsystems with different target levels of design reliability (unit: hours)

Target level of design	Electrical subsystem	Mechanical subsystem
High target level	450643	1236712
Low target level	25708	90472

Monte Carlo simulations are applied to implement the resilience analysis for 4 different cases, i.e. the combination of 2 different target levels of design reliability of wind turbines with 2 different preparedness levels. The expected value of the total benefit of the park within the 30-year service life is illustrated in Figure 6, which increases with the upgrade level of target design reliability and the preparedness. For the park with high design reliability wind turbines, the total benefit is high and correspondingly the influence of preparedness level is insignificant due to the low possibility of the occurrence of the recovery activities. Further, the annual probability of resilience failure for the wind turbine park for different values of χ % for 4 different cases is estimated, and the results are illustrated in Figure 7, each with 1×10^{6} simulations. For the wind turbine park composed of the wind turbines with low target level of design reliability, the probability gradually decreases with the increase of the percentage χ % when χ % is small. As χ % is larger than 35%, the annual probability falls fast in log scale, especially for the park with high preparedness. For the wind turbine park composed of the wind turbines with a high target reliability level, the situation is much better. Only when χ % are low (χ % is less than 5%), the annual failure probability is between and . as χ % is larger than 10%, there is no resilience failure event captured in the 1×10^{6} simulations. Note that here the influence of the target reliability of design on the cost is not considered in the investigation, and therefore, the park with high reliability wind turbines always has low probability of resilience failure due to the relatively less possibility of failure events and the corresponding low demand and consequence by disturbance events.

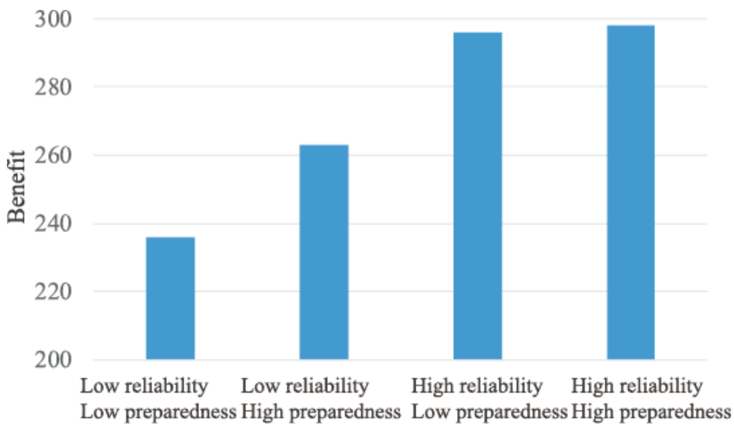

Figure 6: *Expected value of the total benefit of the park within the 30-year service life*

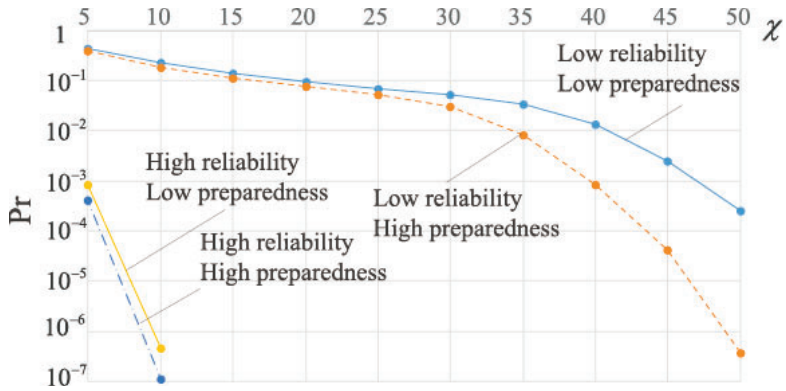

Figure 7: *Annual probability of resilience failure with the variation of the percentage* χ *%*

5 CONCLUSION

In the present paper, a previously developed framework for system resilience modelling and analysis is adapted to wind turbine parks. As the basis of resilience modelling, the system representation of wind turbine parks considers the wind turbines as system of different types of subsystems, i.e. the mechanical subsystem, the electrical subsystem and the structural subsystem, together with the associated uncertainties; while it also illustrates two levels of dependency within the performance of wind turbine parks, i.e. the turbine level of dependency and subsystem level of dependency. Following Faber et al. (2017), the resilience is modelled from a service life perspective to measure whether the capacity of the wind turbine park could sustain the damage by the disturbances and the subsequent repair activities. Considering the special characteristics of the parks, the uncertainties associated with the performance of individual wind turbines, the different levels of dependency within the performance of the parks as well as the damage of different types of subsystem that cause the loss of production of wind turbines are captured in the analysis of the time evolution of benefit and losses of wind turbines over time.

The general idea of approach is illustrated on the resilience analysis of one wind turbine park with 10 wind turbines. From the example, it is demonstrated that decisions on the target reliability of the design of individual wind turbine with respect to disturbance events and operational load may be assessed and optimized to reach requirements in terms of resilience. Moreover, the framework allows decision-making on how much of the utility generated by the system should be kept in reserve as well as what level of preparedness should be achieved to ensure sufficient capacity to recover from the potential disturbances during the service life.

The resilience modelling presented is general, however, for illustrational purpose the system representation of wind turbine parks presented here is rather simplistic. Further detailing accounting for fatigue crack growth and corrosion as well as stock keeping of spare parts and logistical aspects of preventive and corrective maintenance and repairs can and should be included in further developments.

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